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OBESITY INEQUALITY AND THE CHANGING SHAPE OF THE BODYWEIGHT DISTRIBUTION IN CHINA

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Abstract

Using data from the China Health and Nutrition Survey (CHNS), this study analyses changes in bodyweight (BMI and waist circumference) distributions between 1991 and 2011 among adults aged 20+ in China. To do so, we quantify the source and extent of temporal changes in bodyweight and then decompose the increase in obesity prevalence into two components: a rightward shift of the bodyweight distribution (mean growth) and a (re)distributional skewing. Our analysis reveals a clear rightward distributional shift combined with a leftward skewing. Although the relatively large size of this skewing in the first decade analysed reflects an increase in obesity inequality, this inequality growth subsides in the second decade. Nevertheless, over the entire 20-year period, obesity inequality increases significantly, especially among females, younger age groups, rural residents and individuals with low socioeconomic status.

JEL Classification: D30; D63; I10; I14;

Keywords: BMI; Waist circumference; Obesity inequality; Decomposition; China

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1. Introduction

The ever-rising levels of overweight and obesity worldwide make obesity one of the most prominent issues in global public health (Ng et al., 2014), with over 1.9 billion adults aged 18 and older being overweight in 2014 and a further 600 million being actually obese (WHO, 2016). Nonetheless, recent trends in adult obesity rates vary substantially across countries, increasing rapidly in most developing countries like China but slowing or stabilizing in some developed countries such as the U.S. and UK (Lu et al., 2016). In all regions, however, being overweight or obese is linked with an increased prevalence of chronic disease, including cardiovascular disease, stroke, type 2 diabetes and a subset of cancers (Hill and Peters, 1998), as well as particular social and mental health risks (OECD, 2012).

China presents a uniquely interesting case of weight change because of its rapid transition from historical undernutrition to a sharp increase in overweight and obesity (Xi et al., 2012; Zhai et al., 2009). China has also witnessed a major shift in diet – most notably, an increased intake of edible oils, fried foods, animal-sourced foods and snacks – accompanied by a sharp decline in occupational and domestic physical activity (PA), which combination tripled the prevalence of adulthood overweight from 11.7% in 1991 to 29.2% in 2009 (Gordon-Larsen et al., 2014). China's rates of obesity-related non-communicable diseases (NCDs) have also increased dramatically and have become the major risk factors for morbidity, disability and mortality (Popkin, 2008). The country's prevalence of diabetes, for instance, nearly quadrupled between 1994 and 2008 from 2.5% (Pan et al., 1997) to 9.7% (Yang et al., 2010). As a result, China spends 24 billion yuan annually, 2.46% of its annual national health care expenditure, on overweight, obesity and their complications (Qin and Pan, 2016). This expenditure clearly indicates the magnitude of the challenge posed by this rapidly increasing obesity to China's health care system (Zhao et al., 2008).

Statistically, the rise in obesity prevalence (or mean bodyweight) in China can be attributed to two factors: a rightward shift of the bodyweight distribution, indicating that the entire population is growing heavier, or an increase in distributional left-skewness, reflecting more rapid weight gain in one population subset (notably the more obese) and thus rising obesity inequality – or a combination of both. Understanding which is the case is important because the former would call for population-wide policies, whereas the latter would signal a need for policies targeted at groups particularly affected by obesity. Obesity inequality may also play an important role when assessing obesity's persistence: On the one hand, general increases in a population's bodyweight (i.e., a rightward distributional shift) may alter norms and perceptions of ideal bodyweight in the entire population, which can cement higher obesity rates. On the other hand, an increase in distributional skewness, by mainly affecting only a specific portion of the population, may not have such lasting effects. In fact, there is empirical evidence that perceptions of ideal bodyweight are changing. In the U.S., for example, the percentage of overweight (but not obese) individuals who describe their weight as "about right" (rather than "overweight") has increased significantly, from 14% to 21% among women and from 41% to 46% among men (Burke and Heiland, 2018). Blanchflower et al. (2009) also show that, for a given level of overweight, the wider an individual's deviation from the average weight within a region, the stronger his or her feelings of being overweight. Given the large body of evidence on obesity's negative psychological effects (e.g. Katsaiti, 2012), which increase with the deviation from the overall population (Wadsworth and Pendergast, 2014), a rise in obesity inequality could accentuate obesity-related stigma and discrimination.

Yet despite the importance of knowing how a country's bodyweight distribution has changed over time, little research on this topic exists. In fact, we are aware of only four such studies, the first being Contoyannis and Wildman's (2007) analysis of Canadian National Population Health Survey (NPHS) and Health Survey of England (HSE) data, which demonstrates a polarization over time in both nations towards the right-end of the BMI distribution, with the English polarizing towards the upper tails at a faster rate than the Canadians. Subsequent work by Sahn (2009), which draws on Demographic Health Survey data from 30 developing and transitional countries, not only reveals a sharp rise in overweight among women in Latin America and the Middle East but shows that in most countries, female BMI distributions are becoming markedly more unequal. On the other hand, Madden (2011), using 2002–2007 data from the Survey of Lifestyle, Attitudes and Nutrition in Ireland, identifies a marginal decrease in obesity over this period, which he also attributes primarily to a change in the shape of the BMI distribution (as opposed to a change in average level). Lastly, Pak et al. (2016) employ four waves of National Health and Nutritional Examination Survey (NHANES) data to investigate the inter-temporal changes in BMI distribution among U.S. adults between 1971 and 2014. In addition to showing that the early phase of the obesity epidemic is mostly attributable to increasing skewness while recent increases reflect a population-wide increase, these authors demonstrate that within-group inequality accounts for the majority of the increase in obesity inequality, which is worsening over time.

Our study thus aims to provide the first analysis of long-term distributional changes in bodyweight among Chinese adults aged 20+ by examining changes in both the BMI and waist-circumference (WC) distributions over the 1991–2011 period. This approach is important because in China central obesity is much more prominent than general obesity whose negative health effects are less severe (Xi et al., 2012). In addition to applying Kakwani's (1997) technique to decompose total change in obesity prevalence into a mean-growth and a redistribution component, we also employ conventional inequality measures (Gini and generalized entropy) to provide a univariate assessment of obesity inequality. Lastly, we decompose obesity inequality into within-group and between-group to throw light on whether disproportionate obesity increase is a population-wide phenomenon or the result of changing demographic composition.

2. Data and Methods

2.1. Data and study population

The data are taken from 8 waves of the China Health and Nutrition Survey (CHNS) – 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011 – covering nine provinces (Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi and Guizhou) with different social, economic and health characteristics (Zhang et al., 2014). The survey's multi-stage random cluster sampling method (based on different income levels and weighted sampling) entails the following steps: After randomly selecting four counties and two cities within each province, the CHNS randomly identifies villages and towns in each county and urban and suburban regions in each city. It then selects 20 households from each of these communities. The data thus capture a broad spectrum of the spatio-temporal dynamics of the Chinese populations' social, economic and health situations (Zhang et al., 2014).

Our final analytic sample is restricted to adults aged 20 and older for whom detailed demographic, socioeconomic and anthropometric information is available. We exclude from the sample pregnant females; the 1989 wave, which is limited to adults aged 20–45; and the most recent 2015 wave, which provides no anthropometric information. These exclusions leave 8 rounds of CHNS data from 1991 to 2011 and a final sample size of 72,732 BMI observations. When reporting our results, we focus primarily on two periods: 1991-2000 (the early period) and 2000-2011 (the late period). In addition, because waist circumference data are only available from 1993 onwards, for this variable, our early period runs from 1993 to 2000 and our sample size is only 63,493.

2.2 Obesity variables

In the CHNS, weight is measured to the nearest 0.1 kg on a calibrated beam scale with the subject wearing only lightweight clothing, while height is measured to the nearest 0.1 cm using a portable stadiometer with the subject barefoot (Xi et al., 2012). We adopt BMI (in kg/m^2) as one proxy of body weight and define general obesity according to the Working Group on Obesity in China (WGOC) criterion; that is, BMI $\geq$ 28 kg/m^2 (Zhou and the Cooperative Meta-Analysis Group of the WGOC, 2002). Waist circumference (WC) is measured (in cm) at the midpoint between the bottom of the ribs and the top of the pelvis. Abdominal obesity among males is defined as WC $\geq$ 85cm and among females as WC $\geq$ 80cm (Zhou and the Cooperative Meta-Analysis Group of the WGOC, 2002). Our use of CHNS's clinical measures of respondent weight, height and WC is advantageous because it eliminates the reporting bias inherent in self-reported weight and height (Shields et al., 2011), which tends to result in underestimation of BMI (Burkhauser and Cawley, 2008).

2.3 Demographic and socioeconomic variables

To capture subpopulation heterogeneity in obesity inequality, we introduce several demographic and socioeconomic characteristics, including gender (1 = male, 0 = female), age group (20–39 years, 40–59 years and 60+ years), educational level (0 = low: illiterate/primary school, 1 = medium: middle school/high school and 2 = high: technical or vocational degree /university/master's degree or higher), household income level (recoded into terciles: 0 = low, 1 = medium and 2 = high) and region (1 = urban, 0 = rural).

2.4 Methods

Stochastic dominance test. In addition to being common in economic studies of inequality and poverty (Davidson and Duclos, 2003, 2013), the stochastic dominance (SD) test, a non-parametric distributional comparison among continuous variables (Cowell and Flachaire, 2015), is widely used in obesity studies (Madden, 2011; Pak et al., 2016; Sahn, 2009). Applying this intuitively appealing technique to our BMI and WC measures is particularly appropriate given that SD focuses primarily on comparisons over the entire bodyweight distribution and is thus independent of the selection of an obesity threshold (Pak et al., 2016). More specifically, after defining first-order dominance as

$$D_t^1\,(x) = \int_0^x dF_t(y) \qquad (1)$$

we are able to express second-order and higher-order dominance as

$$D_t^s\,(x) = \int_0^x D_t^{s-1}(y)dy, \;\; s \geq 2 \quad (2)$$

We then define $F_{t_n}(x)$ and $F_{t_{n-1}}(x)$ as two cumulative distribution functions (CDF) of our bodyweight measures (BMI and WC), with t_n and t_{n-1} denoting two time points of *n* and *n-1*, respectively. The distribution at time t_n stochastically dominates the distribution at time t_{n-1} at order *s* if the following pair of conditions hold:

$$D_{t_n}^s(x) \leq D_{t_{n-1}}^s(x) \qquad (3)$$

$$D_{t_n}^s(x) < D_{t_{n-1}}^s(x) \qquad (4)$$

where equation 3 indicates that the distribution at time t_n stochastically dominates the distribution at time t_{n-1} at order *s*, and equation 4 indicates the case of strict dominance. In addition to using simple *t*-statistics to test the null hypothesis (H_0: $D_{t_{n-1}}^s(x) - D_{t_n}^s(x) = 0$) for a series of test points along the distribution, we test the significance over the whole bodyweight domain to identify which part of the bodyweight distribution varies most (cf. Pak et al. 2016). Order *s* dominates when the null hypothesis is rejected for at least one test point at the 1% significance level without any reversal in the signs of difference (Madden, 2011). Although the choice of number of test points is quite arbitrary, the more test points used, the more likely the null hypothesis will be rejected, so most studies choose 10 to 30 points (Sahn, 2009; Pak et al. 2016). We alternatively employ 10, 30, 40 and even 80 test points, but our results do not change. Non-dominance exists when the differences are not significant or when the two cumulative distributions cross. Given that the interpretation of higher-order SD is less intuitive (Sahn, 2009) and our focus is on explaining variations in bodyweight distribution, we follow the convention of only analysing the first-order SD test.

Growth-inequality decomposition. Because SD tests can only make comparisons between bodyweight distributions, they say nothing about the underlying mechanisms of upwards or downwards shifts in the bodyweight distribution. We therefore additionally employ Kakwani (1997) decomposition to disentangle the total change in obesity prevalence into a mean-growth and a redistribution component. By doing so, we hope to assess how much of the obesity increase is driven by a horizontal shift in bodyweight distribution (i.e., an increase in mean BMI or WC) and how much by a change in distribution pattern (e.g., an increased skewness towards the upper tail of the BMI or WC distribution) (Pak et al., 2016). Although prior studies employ a variety of methods to decompose poverty into growth and redistribution components (Datt and Ravallion, 1992; Jain and Tendulkar, 1990), these methods all produce an often difficult-to-interpret residual effect, which prevents sole attribution of changes in the measure of interest (in our case, bodyweight) to the growth and inequality effects. Kakwani (1997) describes this latter as the violation of an intuitively natural axiom. A further drawback of these approaches is that the growth and redistribution components differ dependent on choice of reference point, which itself is quite arbitrary (Datt and Ravallion, 1992). Kakwani (1997) thus suggests avoiding such arbitrary choice by using all periods as reference points, a procedure successfully employed in income and health inequality analyses (Christiaensen, 2002; Dhongde, 2007; Sahn and Younger, 2005) that also eliminates the residual term (Sahn, 2009). In our case, the obesity rate at time *t* can be expressed as follows:

$$OB_t = OB(T|m_t; c_t) \tag{5}$$

where OB_t represents obesity prevalence at time t, and T is the obesity threshold (28 for BMI-based obesity, 85cm for male WC-based obesity and 80cm for female WC-based obesity). *m* is the average BMI, and *c* is the Lorenz curve denoting the CDF of the BMI probability distribution.

Changes in obesity rates between t_n and t_{n-1} can be decomposed as

$$OB_{t_n} - OB_{t_{n-1}} = G(t_{n-1}, t_n) + R(t_{n-1}, t_n) + \varepsilon(t_{n-1}, t_n) \tag{6}$$

where $G(\cdot)$, $R(\cdot)$, and $\varepsilon(\cdot)$ represents the growth, redistribution and residual parts, respectively. More specifically, we define the growth and redistribution components as follows:

$$G = OB\left(T\middle|m_{t_n}; c_{t_{n-1}}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_{n-1}}\right) \tag{7}$$

$$R = OB\left(T\middle|m_{t_{n-1}}; c_{t_n}\right) - OB\left(T\middle|m_{t_{n-1}}; c_{t_{n-1}}\right) \tag{8}$$

where G denotes the change in obesity prevalence attributable to a horizontal shift in the bodyweight distribution while the relative position (measured by Lorenz curve) is kept constant. R indicates the observed change in the relative position while the average bodyweight remains constant. Then, following Kakwani (1997), total change in obesity prevalence can be exactly decomposed into the average growth and redistribution effects as follows:

$$OB_{t_n} - OB_{t_{n-1}} = \hat{G}(t_{n-1}, t_n) + \hat{R}(t_{n-1}, t_n) \ (9)$$

where $\hat{G}$ and $\hat{R}$ respectively denote the growth and redistribution components of changes in obesity prevalence as specified by

$$\hat{G} = \frac{1}{2}[OB(T|m_{t_n}; c_{t_{n-1}}) - OB(T|m_{t_{n-1}}; c_{t_{n-1}})] + \frac{1}{2}[OB(T|m_{t_n}; c_{t_n}) - OB(T|m_{t_{n-1}}; c_{t_n})] \ (10)$$

$$\hat{R} = \frac{1}{2}[OB(T|m_{t_{n-1}}; c_{t_n}) - OB(T|m_{t_{n-1}}; c_{t_{n-1}})] + \frac{1}{2}[OB(T|m_{t_n}; c_{t_n}) - OB(T|m_{t_n}; c_{t_{n-1}})] \ (11)$$

In equations 10 and 11, the Kakwani decomposition for two-period comparisons takes an equally weighted average of two decompositions, one in the reference year and the other in a later year. In the case of three periods, we adopt multilateral comparisons to decompose the obesity prevalence into the growth ($\tilde{G}_{ij}$) and redistribution ($\tilde{R}_{ij}$) effects (Kakwani, 1997):

$$\tilde{G}_{ij} = \frac{1}{n}\sum_{k=1}^{n}(\hat{G}_{ik} + \hat{G}_{kj}) \qquad (12)$$

$$\tilde{R}_{ij} = \frac{1}{n}\sum_{k=1}^{n}(\hat{R}_{ik} + \hat{R}_{kj}) \qquad (13)$$

where i and j range from 1 to n (in our case, n=3), and $\hat{G}_{ij}$ and $\hat{R}_{ij}$ follow the same specifications as in equations (10) and (11).

Obesity inequality measures (Gini and generalized entropy). Although SD tests provide partial rankings of bodyweight distributions, they do not identify cardinal distributional differences. At the same time, the Kakwani technique used to decompose the total change in obesity rates is heavily dependent on the selection of an obesity threshold (Pak et al., 2016). Therefore, as a complementary approach, we also introduce Gini and generalized entropy (GE) measures to track the cardinal changes in obesity inequality. The Gini coefficient, a measure of statistical dispersion in a particular distribution, is a popular and widely used index measuring inequality (Yitzhaki, 1983). In essence, the Gini index, which ranges from 0 (complete equality) to 1 (complete inequality), is twice the area between the Lorenz curve and the 45-degree line (Cowell and Flachaire, 2015). Following Pak et al. (2016), we express this measure as

$$Gini_t = \frac{2}{m_t N_t^2}\sum_{i=1}^{N_t} BMI_{it} r_{it} - \frac{N_t + 1}{N_t} \qquad (14)$$

where *N* is the sample size, *m* is the average BMI, BMI_{it} is the individual BMI value at time *t*, and r_{it} denotes the ranking of *i*th BMI at time *t* in ascending order (with an equivalent expression for WC).

Because the Gini index is sensitive to changes around the distributional mode, we also adopt GE measures that are flexible enough to allow greater sensitivity away from the distributional middle (Shorrocks, 1984; Yang, 1999). We express the GE index as

$$GE_t(\omega)\frac{1}{w(w-1)}[\frac{1}{N_t}\sum_{i=1}^{N_t}(\frac{BMI_{it}}{m_t})^w - 1] \qquad (15)$$

where ω is a scaling parameter representing the weight given to distances between individual BMI at different parts of the BMI distribution (with the same equation used for WC). The mean logarithmic deviation (MLD) is the limiting case when $\omega = 0$ (GE(0)), while the Theil index is the limiting case when $\omega = 1$ (GE(1)) (Cowell and Flachaire, 2015), which assures equal treatment of the differences between individual BMI levels at different parts of the BMI distribution. GE(2) is half the square of the coefficient of variation (Jenkins and Kerm, 1999). Because these GE(ω) indices vary in their sensitivities to differences in different distributional areas, the more positive (negative) the ω, the more sensitive GE(ω) to BMI differences at the top (bottom) of the distribution (Jenkins and Kerm, 1999). As robustness checks, we also set ω to 0 and 2, thereby enabling comparisons with Pak et al.'s (2016) outcomes for the U.S. population.

The use of SD tests and the Kakwani decomposition alone, however, does not allow us to identify which changes in obesity inequality are driven by changing subpopulation characteristics and which by a population-wide shift in bodyweight distribution. Rather, for this task, we introduce a GE-based decomposition by subgroup that splits the GE index into within-group and between-group inequality (Shorrocks, 1984):

$$GE_t(\omega) = GE_t(\omega)_{within-group} + GE_t(\omega)_{between-group} \qquad (16)$$

$$GE_t(\omega)_{within-group} = \sum_j \frac{BMI_{t,j}}{BMI_t} GE_{t,j} \qquad (17)$$

$$GE_t(\omega)_{between-group} = \sum_j \frac{BMI_{t,j}}{BMI_t} \ln(\frac{BMI_{t,j}/BMI_t}{N_{t,j}/N_t}) \qquad (18)$$

where $GE_{t,j}$ and $BMI_{t,j}$ represent the GE index and BMI at subgroup *j* and time *t*, respectively (with a similar approach applied for WC). In equation 16, the first term denotes the weighted sum of inequality within groups, while the second term designates the component driven by the heterogeneity in inequality between groups. We calculate this latter by assuming that everyone within a group has that group's mean bodyweight. From this expression, we can thus obtain the proportion of total bodyweight inequality attributable to inequality within groups and the proportion attributable to inequality between groups. If the relative contribution of total bodyweight inequality attributable to between-group inequality is negligible and the change of within-group inequality across time is comparable over groups, then the increasing bodyweight inequality is probably not driven by changes in the population's demographic composition but by changes in the population at large (Pak et al., 2016). To detect possible heterogeneities in population subgroups, we also perform a decomposition of the Theil index by age, gender, education, household income and region, as well as combinations of these categories.

3. Results

As shown by the Fig.1 illustration of the BMI kernel density and CDF curve between 1991 and 2011, not only did the BMI distribution generally shift to the right but the prevalence of obesity prevalence (BMI $\geq$ 28 kg/m^2) increased significantly from 3.2% in 1991 to 11.6% in 2011. The same pattern is evident for WC (Fig. 2), with the prevalence of central obesity increasing from 24.4% in 1993 to 56.4% in 2011. Taken together, these observations confirm that our analysis covers the start of the obesity epidemic. Nonetheless, it is also worth noting that the obesity prevalence in China is still much lower than that in the U.S. four decades ago and that as yet, extreme obesity (i.e., BMI $\geq$ 40 kg/m^2) is still not a major problem in China.

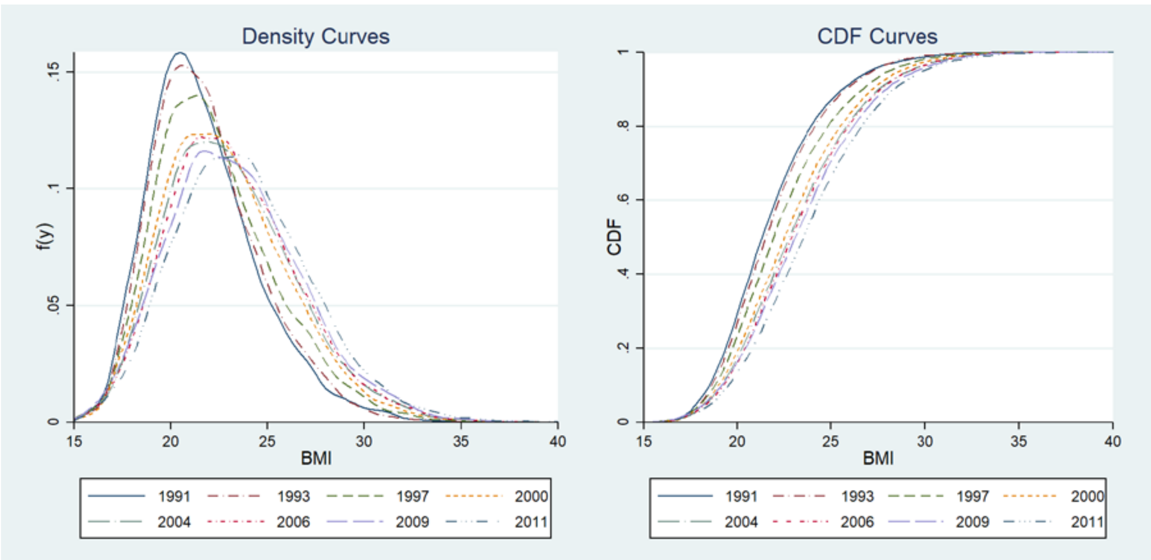

Fig.1 BMI distribution over time, 1991–2011

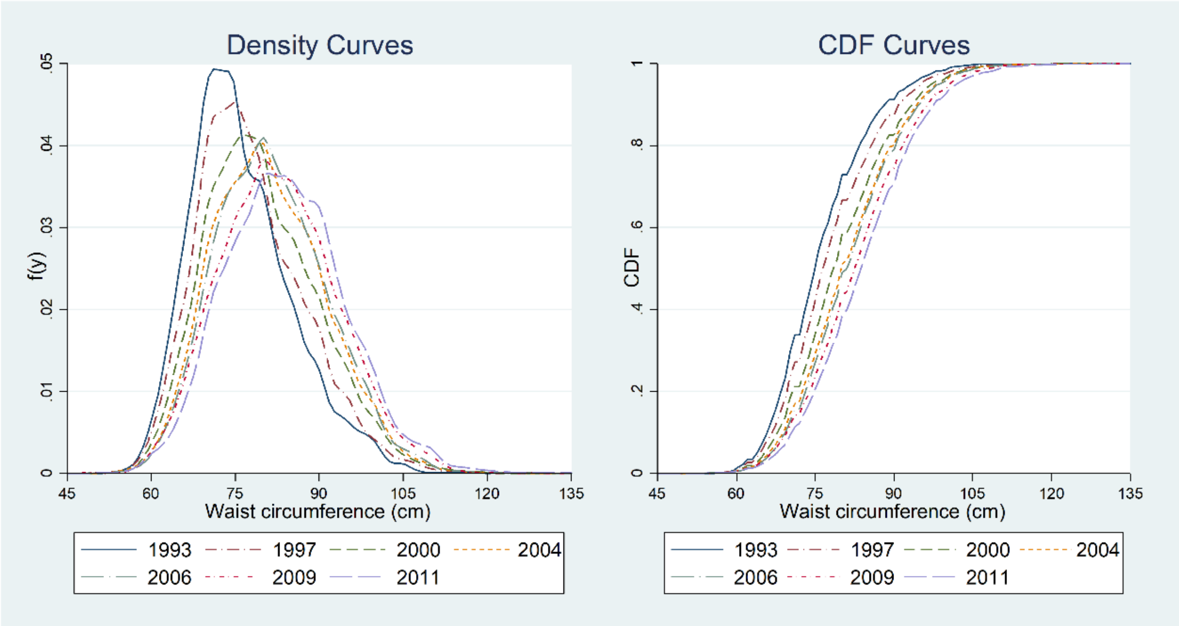

Fig.2 WC distribution over time, 1993–2011

Because exact assessment of CDF differences is difficult, in Figs. 3 and 4, we graph the differences for different periods, revealing a clear rightward shift in the BMI distribution. The mostly negative CDF differences responsible for this shift reflect an increase in bodyweight, with the largest negative values encountered at a BMI of around 23 and a WC of approximately 79. The shift thus indicates a significant reduction in the proportion of individuals with normal bodyweight, one that is most evident in the differences between 1991 and 2011. Over these two decades, the probability of having a BMI (WC) under 23 (80) dropped by close to (more than) 30 percentage points.

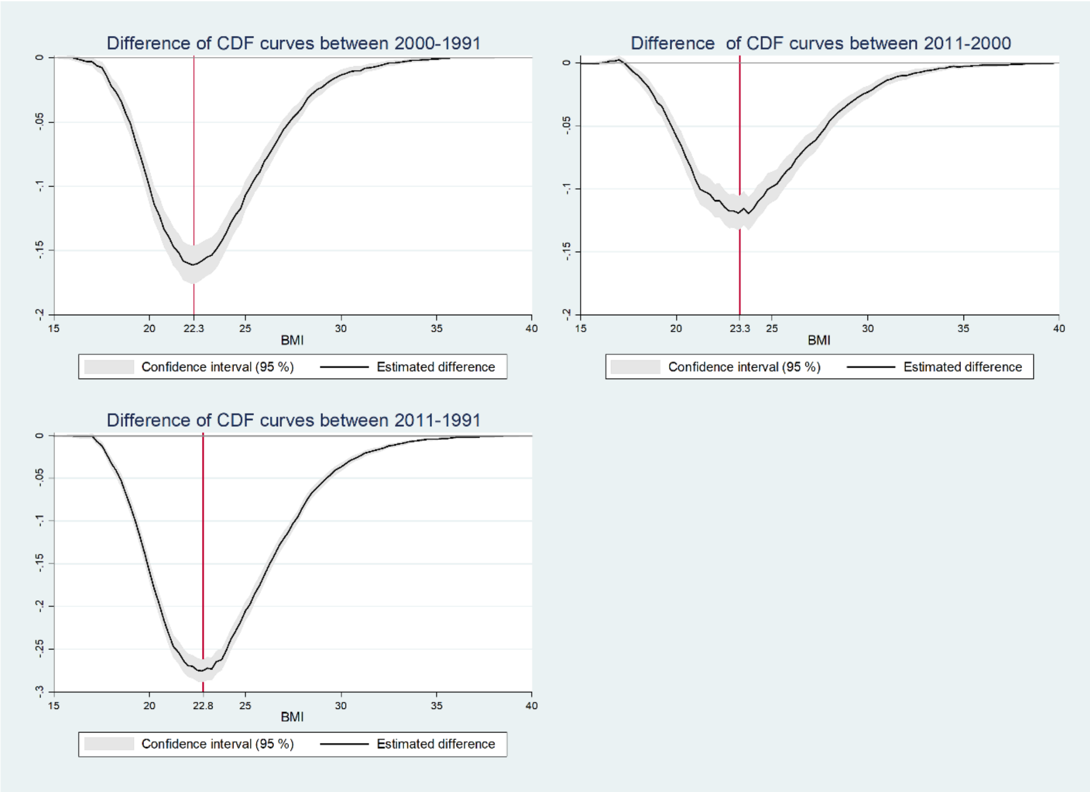

Fig. 3 Differences in the BMI CDF curve: 2000–1991, 2011–2000 and 2011–1991

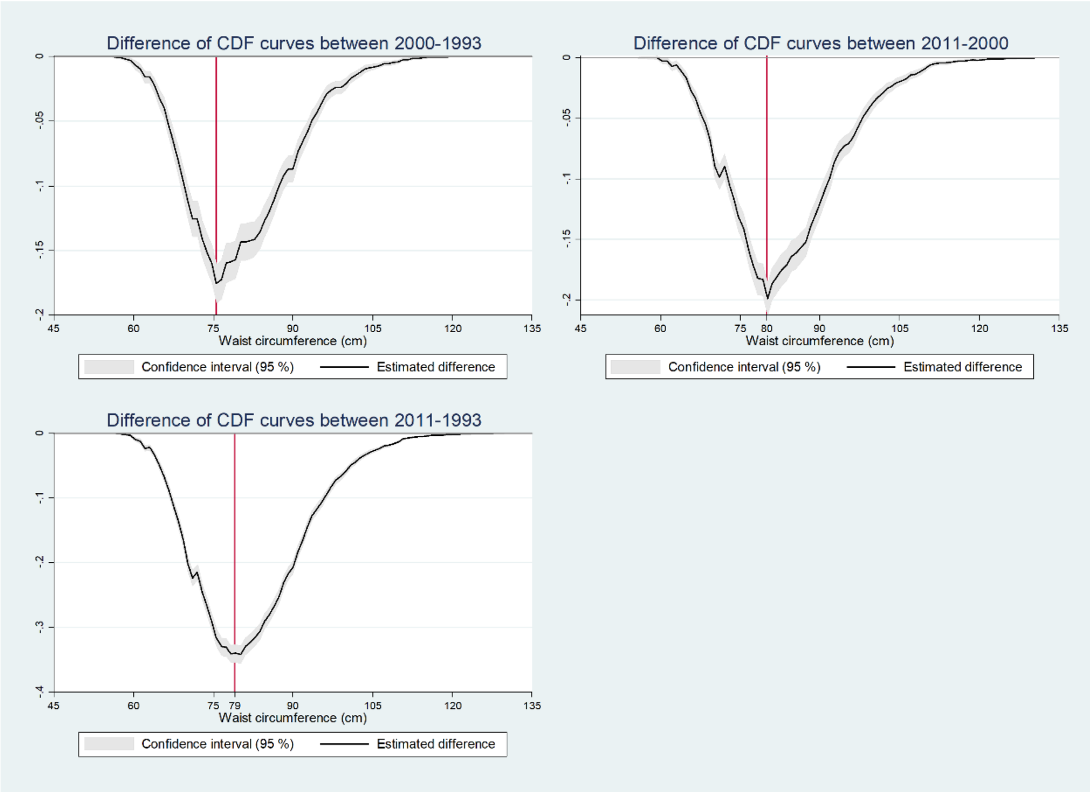

Fig. 4 Differences in the WC CDF curve: 2000–1993, 2011–2000 and 2011–1993

The results in Table 1 also reveal a first-order stochastic dominance for all wave-to-wave comparisons, as well as for the periods 1991(1993)–2000, 2000–2011 and 1991(1993)–2011. Because the first-order SD tests are in essence based on comparisons of the CDF curves in two distributions, this first-order stochastic dominance is reflected in the predominantly negative values in Figs. 3 and 4.

Table 1 First-order stochastic dominance test for BMI and WC

Survey Year	Dominance Test BMI	Dominance Test WC
1991-1993	1	
1993-1997	1	1
1997-2000	1	1
2000-2004	1	1
2004-2006	1	1
2006-2009	1	1
2009-2011	1	1
1991 (1993)-2000†	1	1
2000-2011	1	1
1991 (1993)-2011†	1	1

Note: 1 designates first-order stochastic dominance.
†WC data only available for 1993–2011.

In addition to the stochastic dominance test, deriving the growth incidence curve can provide insights into the magnitude of the bodyweight increase and describe which part of the bodyweight distribution contributes more to the overall growth between two periods. The growth incidence curves in Fig. 5 therefore show the percentage change at each percentile, with the horizontal line representing the mean growth rate. Whereas the early period is marked by significant distributional skewing with BMI growth not only higher at the upper end but above average in most of the upper half; in the later period, the growth incidence curve becomes flatter with very few significant growth rate differences across the distribution. Only below the 20th percentile do we observe significantly lower growth rates than the average. Fig. 5 thus reveals a growing inequality (i.e., an increase in distributional left-skewness) at the end of the last century followed by a more equal rise in BMI at the beginning of this century. In fact, there is clear evidence of ongoing skewing over the entire 20 years caused by above average BMI growth in the upper parts of the distribution. The pattern for the WC growth incidence curves is similar to those for BMI (Fig. 6). Also evident over the entire period are below-average growth rates below the 20th percentile. This pattern of rising inequality in the early stages of the obesity epidemic followed by more equal growth rates in the entire population to some extent mirrors developments in the U.S., in which significant distributional left-skewing between 1976–1994 (i.e., in the early stages of the obesity epidemic) is followed in the next decade by relatively equal growth rates across the entire distribution (Pak et al., 2016).

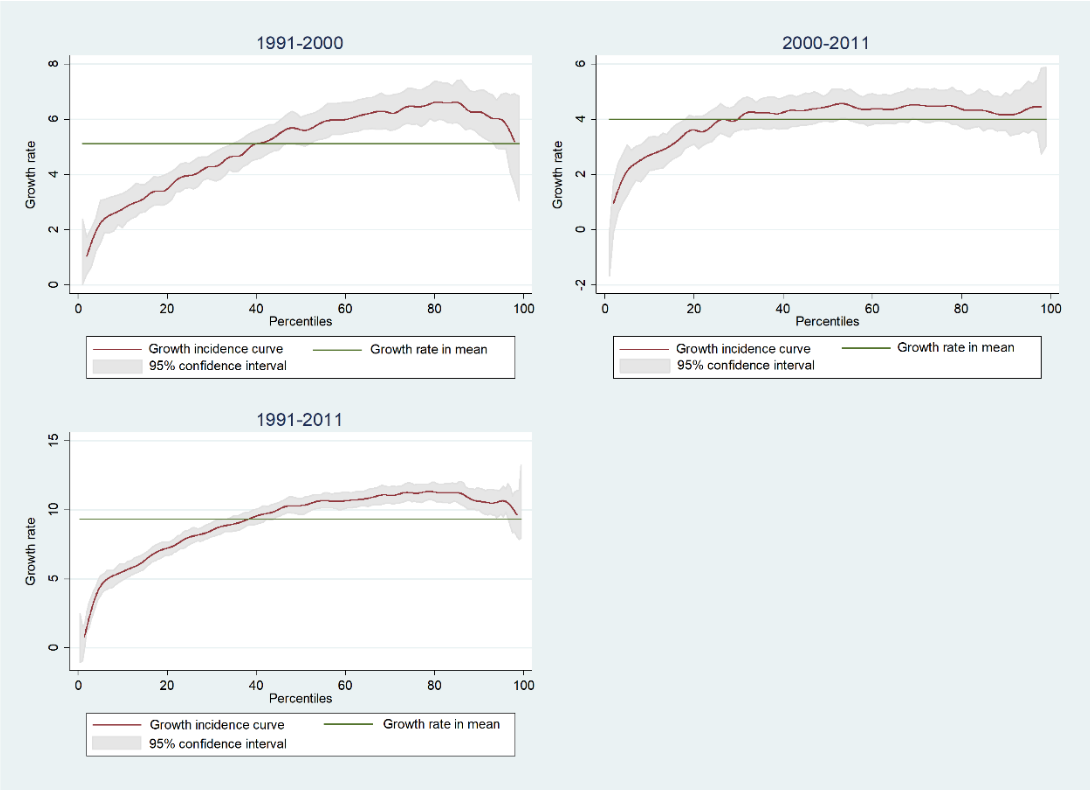

Fig. 5 BMI growth incidence curves

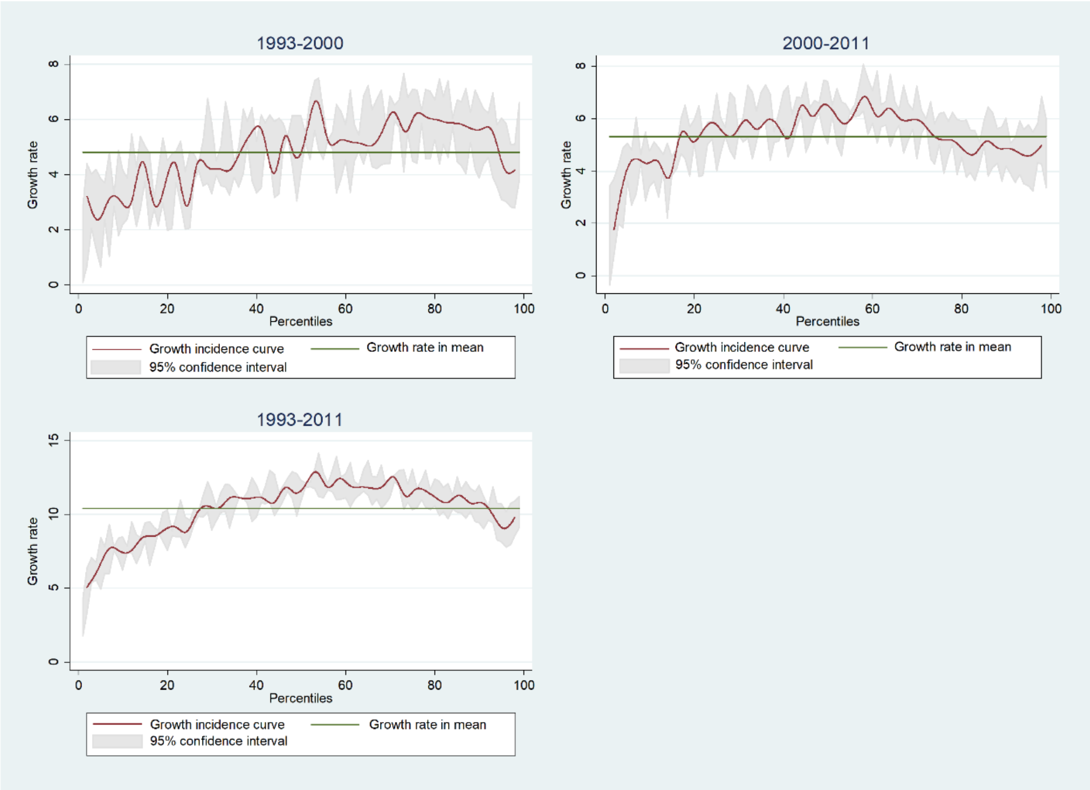

Fig. 6 WC growth incidence curves

Using Kakwani (1997) decomposition to partition the total changes in obesity prevalence into a growth and redistribution component also allows us to quantify how much of the obesity increase is due to rightward distributional shift and how much to distributional skewing. As Table 2 shows, in the early period, general (BMI-based) obesity rose by 3.78 percentage points, 84% of it attributable to the growth component and about 16% to distributional skewing. Hence, although the rising inequality in the early period (as shown in Fig. 5) significantly affected the rise in obesity rates, the general mean growth in BMI was more important. The flattening of the growth incidence curves in Fig. 5 is also mirrored by the redistribution component's drop in importance in the later period to a mere 8%. Over the entire two decades, about 11% of the 8.37% point increase in obesity is attributable to distributional skewing; that is, to the rise in obesity inequality.

Table 2 Decomposition of increase in general obesity prevalence into mean-growth and redistribution components

Survey year	Difference	Growth component (G)	Redistribution component (R)	G/(G+R) (%)	R/(G+R) (%)
1991-2000	0.0378	0.0317	0.0061	83.86	16.14
		(0.0011)	(0.0017)		
2000-2011	0.0459	0.0423	0.0036	92.16	7.84
		(0.0014)	(0.0021)		
1991-2011	0.0837	0.0741	0.0096	88.53	11.47
		(0.0025)	(0.0037)		

Note: Standard errors are in parentheses.

Because assessments of central obesity apply different obesity thresholds for men and women, Table 3 reports the Kakwani (1997) decomposition for both genders. In the early period, the prevalence of central obesity among men rose by 16% points, 17% of it due to redistribution. In the later period, the prevalence increased by another 20% points, while the redistributive components declined to 6%. Over the entire study period (1993–2011), central obesity increased by 37% points among men, about 11% of it attributable to redistribution, whereas the rise among women, at 28% points, was lower, with about 10% of it due to redistribution.

Table 3 Decomposition of increase in central obesity prevalence into mean-growth and redistribution components

Gender	Survey year	Difference	Growth component (G)	Redistribution component (R)	G/(G+R) (%)	R/(G+R) (%)
Male	1993-2000	0.1644	0.1367	0.0277	83.15	16.85
			(0.0038)	(0.0043)		
	2000-2011	0.2021	0.1890	0.0131	93.52	6.48
			(0.0043)	(0.0048)		
	1993-2011	0.3665	0.3257	0.0408	88.87	11.13
			(0.0081)	(0.0090)		
Female	1993-2000	0.1226	0.1147	0.0079	93.56	6.44
			(0.0036)	(0.0053)		
	2000-2011	0.1554	0.1370	0.0184	88.16	11.84
			(0.0040)	(0.0043)		
	1993-2011	0.2781	0.2517	0.0264	90.51	9.49
			(0.0077)	(0.0097)		

Note: Standard errors are in parentheses.

Because Kakwani decomposition has the disadvantage of being highly dependent on the obesity cut-off value, however, it offers little in the way of a differentiated look at the entire BMI distribution. We overcome this weakness by using a univariate concentration index that tracks the cardinal growth of obesity inequality. According to Table 4, both the Gini and GE indices have risen in the two decades under analysis, indicating that general obesity inequality has increased. More specifically, the Gini value rose from 0.0724 in 1991 to 0.0791 in 2000 to 0.0823 in 2011, about a 14% increase across the entire two decades. Over the same time period, the GE index increased only moderately, while the magnitudes of the two GE indices – GE(0) and GE(2) – remained quite comparable. These observations imply that our finding of increasing obesity inequality is very robust irrespective of the relative importance attributed to the lower or upper tails of the distribution. The results for inequality in central obesity are quite similar, with the Gini index increasing from 0.0654 to 0.0708 between 1993 and 2011.

Table 4 Inter-temporal trends in obesity inequality

Survey year	Gini index	95% CI	Difference between t and t-1	% change between t and t-1	Sensitivity analysis	
					GE(0)	GE(2)
BMI						
1991	0.0724	0.0712-0.0736			0.0083	0.0087
2000	0.0791	0.0779-0.0802	0.0067***	9.2541	0.0098	0.0101
2011	0.0823	0.0812-0.0833	0.0032***	4.0455	0.0106	0.0108
1991-2011			0.0099***	13.6740		
WC						
1993	0.0654	0.0643-0.0665			0.0067	0.0069
2000	0.0695	0.0686-0.0705	0.0041***	6.2691	0.0075	0.0077
2011	0.0708	0.0699-0.0717	0.0013***	1.8705	0.0079	0.0079
1993-2011			0.0054***	8.2569		

Note: CI denotes 95% confidence intervals; GE refers to generalized entropy. *** indicates 1% significance in the t-test for differences between the inequality indexes for two different sampling periods.

The rise in inequality is also evident in Figs. 7 and 8, which plot the Gini coefficient for all waves based on different socioeconomic and demographic characteristics. Both males and females have experienced a sharp growth in obesity inequality, although that among females is uniformly higher than that among males. On the other hand, despite a significant rise in obesity inequality among younger adults (aged 20–39), the change among older adults (aged 40–59 and 60+) has remained stable. One striking development is the significant rise in obesity inequality in rural areas, which has now surpassed that in urban areas. With regards to education, we observe that unequal growth is particularly associated with lower educational levels (illiterate and primary school), although this growth is more pronounced for BMI than WC. It should also be noted that if bodyweight levels differ significantly between genders, the Gini coefficient is dependent on the gender balance within an educational or income category. As this unequal balance is particularly true for WC, we also report gender-specific figures for education and income. In terms of income, obesity inequality has risen in all income categories but is highest among lower income individuals.

Overall, therefore, obesity inequality appears to be on the rise in most socioeconomic and demographic groups but is particularly high among women, individuals with lower socioeconomic status, and those living in rural areas. According to the growth incidence curves for these different demographic and socioeconomic groups (Appendix Figs. A1-A10), this rise in inequality is clearly being driven by distributional left-skewing, especially for the younger age group (20–39), rural residents and individuals with low and medium education and income.

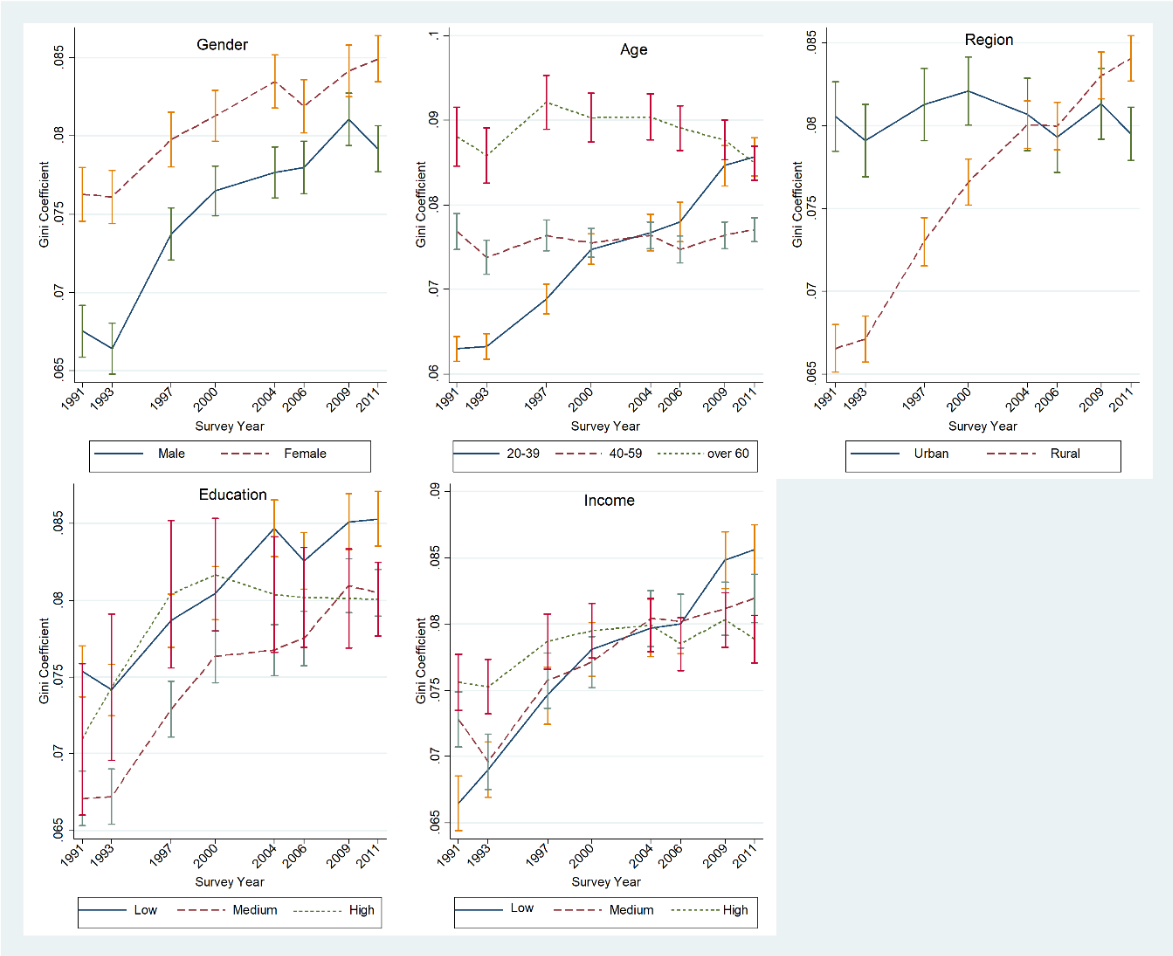

Fig. 7 Trend in general obesity inequality (Gini index) by gender, age, region, education and income, 1991–2011

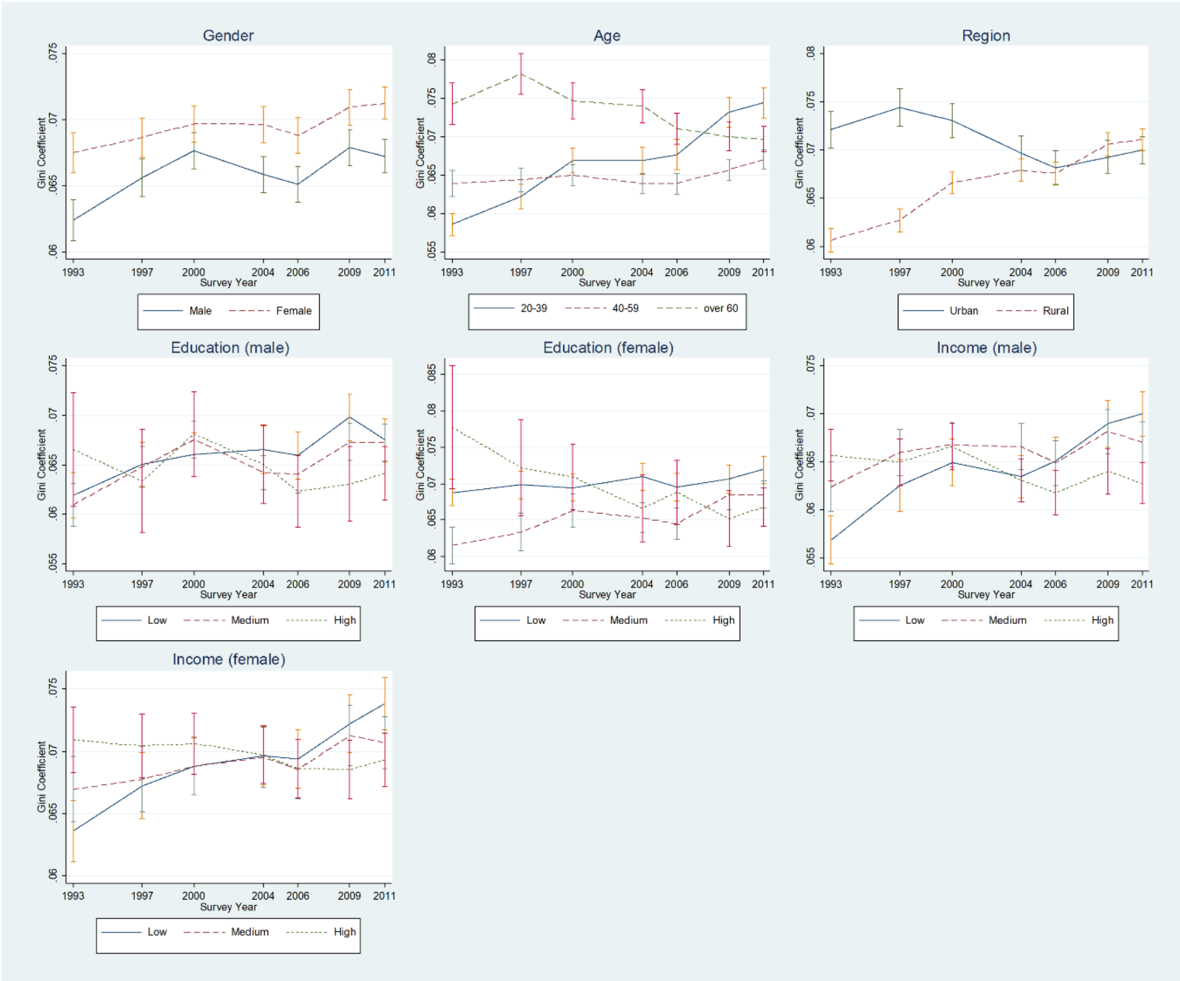

Fig. 8 Trend in central obesity inequality (Gini index) by gender, age, region, education and income, 1993–2011

Although the development of general obesity inequality is somewhat similar to that of central obesity inequality, both inequality and growth rates are larger in the former than in the latter (see Figs. 7 and 8, respectively). Hence, to throw more light on the drivers of general obesity inequality, Table 5 decomposes it into within-group and between-group components. Because Table 4 indicates no significant discrepancy between GE(0) and GE(2), we adopt the Theil index (GE(1)) to decompose obesity inequality by gender, age, education, household income, and region (urban vs. rural), as well as combinations of these characteristics. After adjusting for gender, age, region, education and income, general obesity inequality is mostly attributable to within-group inequality, whose degree – at between 91.1% and 94.0% – remains reasonably stable during the period studied. Relative to within-group inequality, the contribution of between-group inequality to total inequality is small, accounting for 6.0-9.0% of total obesity inequality once gender, age, education, household income and region are controlled for. Of these latter characteristics, region and income account for most of the between-group inequality (0.3%-3.0% and 0.4%-2.7%, respectively). Overall, relative to between-group inequality, the dominance of within-group inequality to total obesity inequality over time suggests that this disproportionate shift in the BMI distribution is not mainly due to a changing demographic and socioeconomic composition of the population, but rather to a population-wide pattern. This conclusion also applies to central obesity inequality (Table 6), although the contribution of between-group inequality to total inequality is slightly higher, ranging from 11.75% to 13.73%.

Table 5 Within-group and between-group general obesity inequality, GE (1)

Survey year	GE(1)		Gender	Age	Region	Income	Education	Gender/age/ region/income/ education
1991	0.0084	Within	0.9948	0.9842	0.9761	0.9733	0.9957	0.9106
		Between	0.0052	0.0158	0.0239	0.0267	0.0043	0.0894
1993	0.0082	Within	0.9958	0.9822	0.9817	0.9890	0.9983	0.9270
		Between	0.0042	0.0178	0.0183	0.0110	0.0017	0.0730
1997	0.0093	Within	0.9978	0.9879	0.9706	0.9826	0.9975	0.9144
		Between	0.0022	0.0121	0.0294	0.0174	0.0025	0.0856
2000	0.0097	Within	0.9987	0.9821	0.9851	0.9817	0.9994	0.9171
		Between	0.0013	0.0179	0.0149	0.0183	0.0006	0.0829
2004	0.0103	Within	0.9993	0.9813	0.9899	0.9823	0.9996	0.9184
		Between	0.0007	0.0187	0.0101	0.0177	0.0004	0.0816
2006	0.0101	Within	0.9999	0.9846	0.9932	0.9894	0.9994	0.9222
		Between	0.0001	0.0154	0.0068	0.0106	0.0006	0.0778
2009	0.0107	Within	0.999993	0.9771	0.9960	0.9904	0.9997	0.9272
		Between	0.000007	0.0229	0.0040	0.0096	0.0003	0.0728
2011	0.0107	Within	0.9997	0.9825	0.9970	0.9962	0.9982	0.9403
		Between	0.0003	0.0175	0.0030	0.0038	0.0018	0.0597

Note: Age groups = 20–39, 40–59, 60 and over; gender = male, female; region = urban, rural; income = low, middle and high; education = low (illiterate/primary school), medium (middle school/ high school) and high (technical or vocational degree /university/master's degree or higher).

Table 6 Within-group and between-group central obesity inequality, GE (1)

Survey year	GE(1)		Gender	Age	Region	Income	Education	Gender/age/region/income/education
1993	0.0068	Within	0.9922	0.9413	0.9740	0.9896	0.9909	0.8734
		Between	0.0078	0.0587	0.0260	0.0104	0.0091	0.1266
1997	0.0072	Within	0.9787	0.9579	0.9669	0.9884	0.9959	0.8685
		Between	0.0213	0.0421	0.0331	0.0116	0.0041	0.1315
2000	0.0075	Within	0.9749	0.9571	0.9794	0.9858	0.9984	0.8627
		Between	0.0251	0.0429	0.0206	0.0142	0.0016	0.1373
2004	0.0074	Within	0.9724	0.9593	0.9916	0.9848	0.9997	0.8636
		Between	0.0276	0.0408	0.0084	0.0152	0.0003	0.1364
2006	0.0072	Within	0.9716	0.9652	0.9921	0.9895	0.9999	0.8753
		Between	0.0284	0.0348	0.0079	0.0105	0.0001	0.1247
2009	0.0077	Within	0.9762	0.9581	0.9945	0.9888	0.9989	0.8809
		Between	0.0238	0.0419	0.0055	0.0111	0.0011	0.1191
2011	0.0079	Within	0.9614	0.9702	0.9954	0.9970	0.9993	0.8825
		Between	0.0387	0.0299	0.0046	0.0030	0.0007	0.1175

Note: Age groups = 20–39, 40–59, 60 and over; gender = male, female; region = urban, rural; income = low, middle and high; education = low (illiterate/primary school), medium (middle school/ high school) and high (technical or vocational degree /university/master's degree or higher).

4. Conclusions

Even though knowing how bodyweight distributions have changed over time is crucial to understanding the nature of the rising obesity prevalence, this present study is the first to examine such changes in China's adult population. This knowledge is vital because, just as the social welfare implications of rising national income differ greatly dependent on whether induced by rapid income growth among the rich (i.e., rising income inequality) or across the entire population, so policy responses to rising obesity must vary according to whether driven by rapid growth at the upper ends of the bodyweight distribution or a general rightward distributional shift. In addition, although obesity inequality is generally recognized as an important indicator of well-being – a multidimensional domain that at minimum encompasses not only income but health, nutrition and education – measures of social inequality still focus almost exclusively on income or expenditure. Obesity inequality is thus empirically interesting as a measure capable of capturing the allocation of resources (primarily food) across individuals relative to their individual needs (Sahn, 2009).

Overall, by using 20 years of CHNS data (1991–2011), our study sheds valuable light on the exact nature of the rise in China of both central and general obesity. In particular, our results clearly demonstrate a significant rightward shift in both the BMI and WC distributions, with first-order stochastic dominance for all wave-to-wave comparisons. Over the two decades under analysis, about 90% of the rise in both general and central obesity is attributable to this rightward shift. On the other hand, the analysis also reveals a certain degree of distributional left-skewing, which reflects increased obesity inequality, about a 14% and 8% increase in the Gini coefficient for general and central obesity, respectively. Nonetheless, the 2011 Gini coefficients of 0.08 and 0.07 for general and central obesity, respectively, suggest that although obesity inequality had risen, it is still much lower than in the U.S., whose general obesity coefficient that year was about 0.13 (Pak et al., 2016). As in the U.S., however, the rise in obesity inequality in China has been particularly large among younger age groups and women. We also document a very strong increase in obesity inequality among rural residents and individuals with lower socioeconomic status (low education and income). Nevertheless, the rise in aggregate inequality is not being driven by changes in the demographic structure but rather by a population-wide increase across all subpopulations.

When comparing our results with those of Pak et al. (2016) for the U.S., we observe an interesting similarity in the transition from the early to later stages of the obesity epidemic (i.e., from low to high obesity prevalence); that is, in the early years, obesity inequality rose quite rapidly due primarily to a disproportionate rise at the upper end of the bodyweight distribution. This pattern is also evident in Sahn's (2009) analysis of over 70 nationally representative surveys from developing countries. Once the epidemic has broadened, however, the growth in inequality declines. To some extent, this development parallels the evolution of infectious diseases: at its onset, the epidemic disproportionally affects the most vulnerable, which in the case of obesity are those already at the upper ends of the BMI distribution. Given a broad body of evidence that these individuals are particularly susceptible to peer effects (e.g., Nie et al., 2015), bodyweight increases among this group tend to spread quickly. As this process continues and the condition spreads, then all portions of the population become affected and "inequality" becomes less of an issue.

This transitional pattern from low to high obesity has important implications for obesity's consequences: First, rising inequality levels in the early transition can have a particularly strong effect on the well-being of individuals at the right tail of the bodyweight distribution whose bodyweight tends to increase more quickly than the population average and is thus more likely to deviate from the socially perceived ideal. Indeed, much evidence exists that obesity's negative effects on well-being depend on the extent of the deviation from peer bodyweights (Wadsworth and Pendergast, 2014). Thus, policy interventions to combat obesity during the early transition should primarily target the groups experiencing the most rapid growth in inequality. Focusing on such groups is also important to avoid spill-overs from strong peer effects at the upper end of the bodyweight distribution that could lead to rising obesity levels (i.e., a rightward distributional shift). Targeted policy interventions could thus profit from the so-called social multiplier effect (Fletcher, 2011); that is, the externality inherent in peer effects. As the epidemic spreads and obesity becomes a population-wide phenomenon, however (represented mainly by a rightward distributional shift), norms and ideals begin to change, making higher bodyweight levels more socially acceptable and even desirable. Then, not only do obesity's stigmatizing effects become less of an issue, but the changing norms and ideals contribute strongly to its persistency, making policy interventions less effective.

According to our analysis, China is well into the transition phase: obesity prevalence has risen substantially (especially in the case of central obesity), and, after a rapid rise, inequality growth is declining. The time has thus come to implement interventions targeted at specific groups whose obesity inequality is still growing as a particularly rapid pace; most notably, women, youth, rural residents, and individuals with lower socioeconomic status.

Conflict of interest

None.

Funding source

None.

Acknowledgments

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Appendix

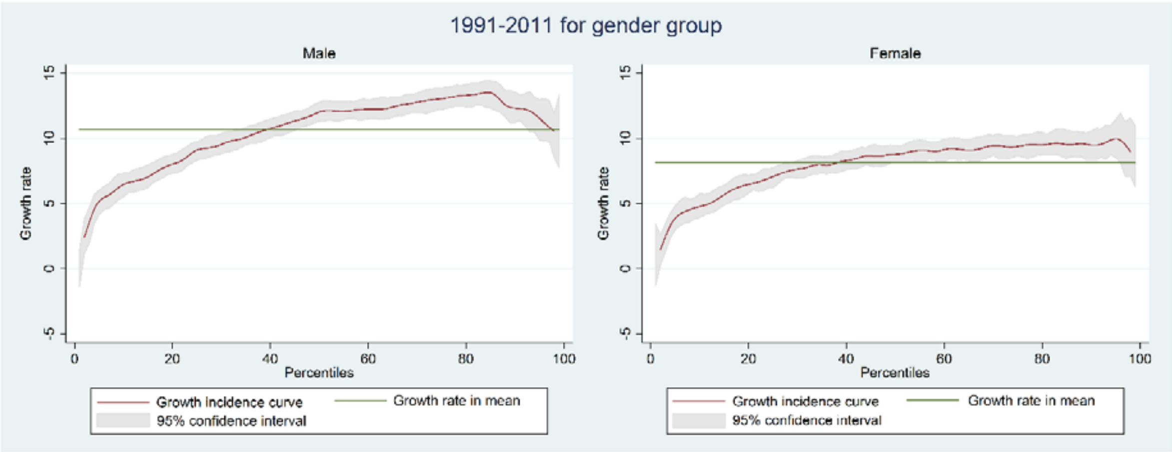

Fig. A1 BMI growth incidence curves by gender

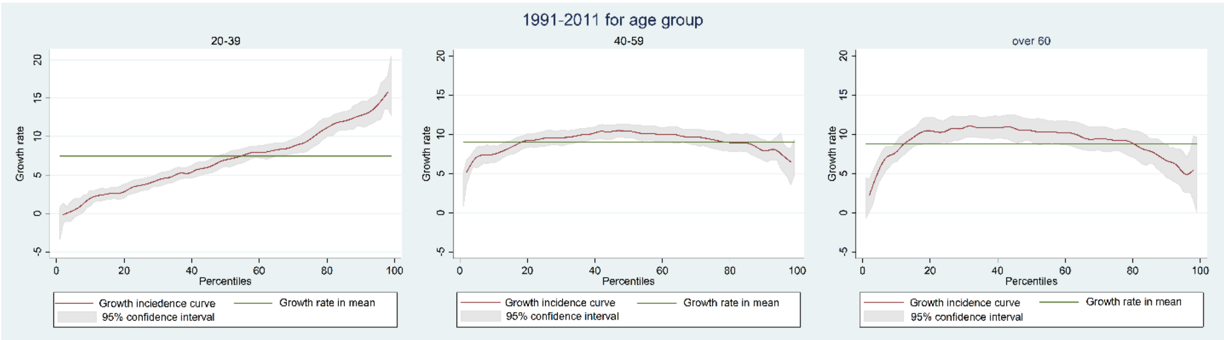

Fig. A2 BMI growth incidence curves by age groups

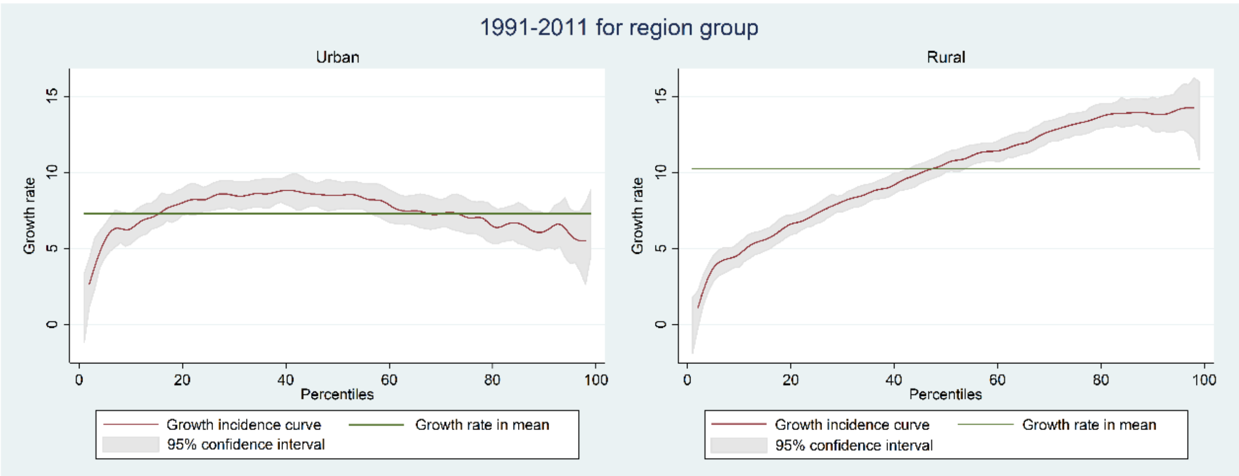

Fig. A3 BMI growth incidence curves by region

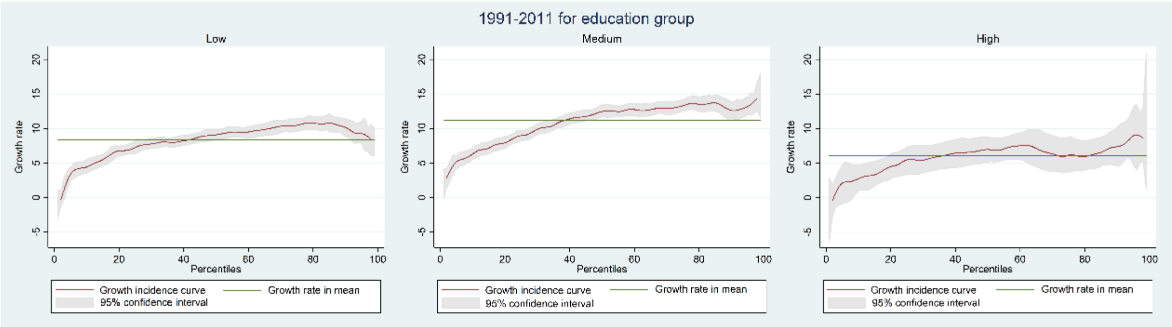

Fig. A4 BMI growth incidence curves by education

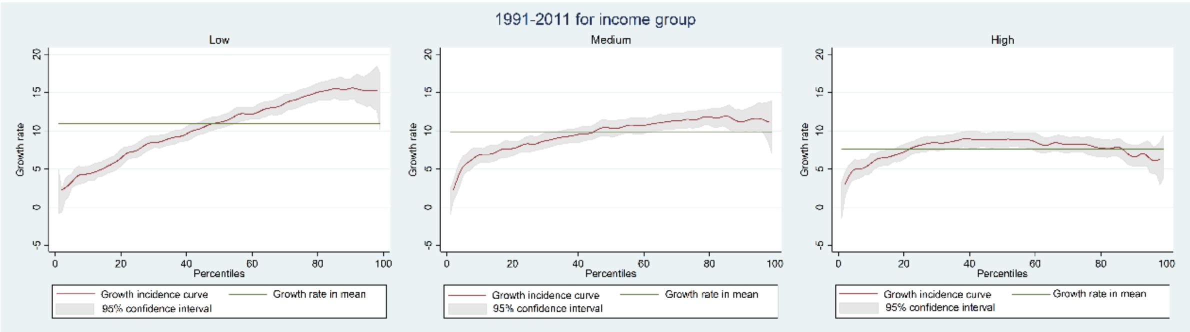

Fig. A5 BMI growth incidence curves by income

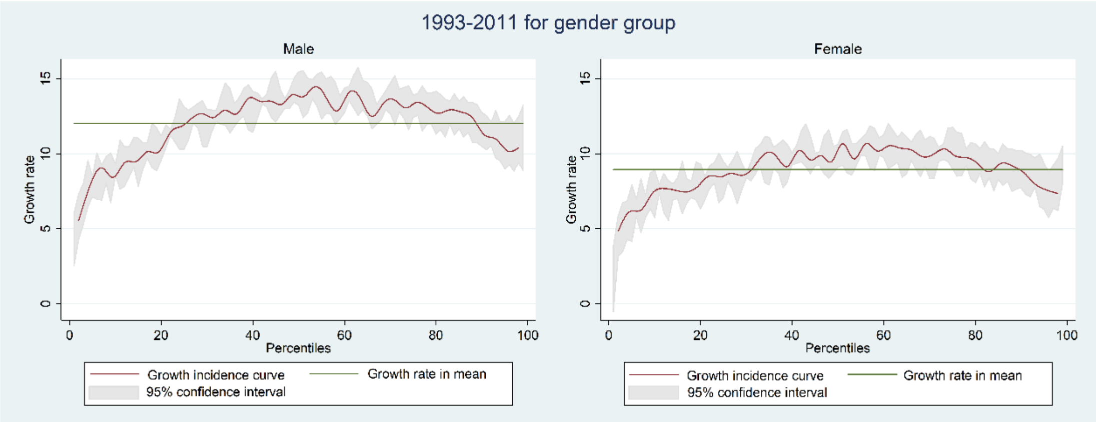

Fig. A6 WC growth incidence curves by gender

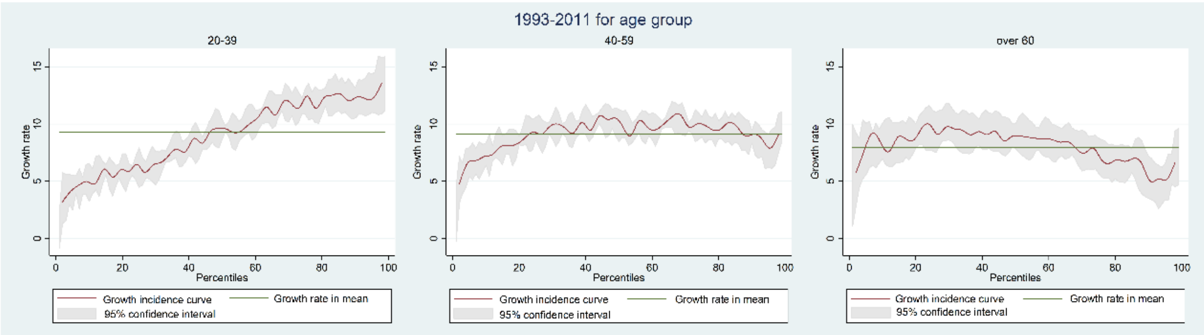

Fig. A7 WC growth incidence curves by age groups

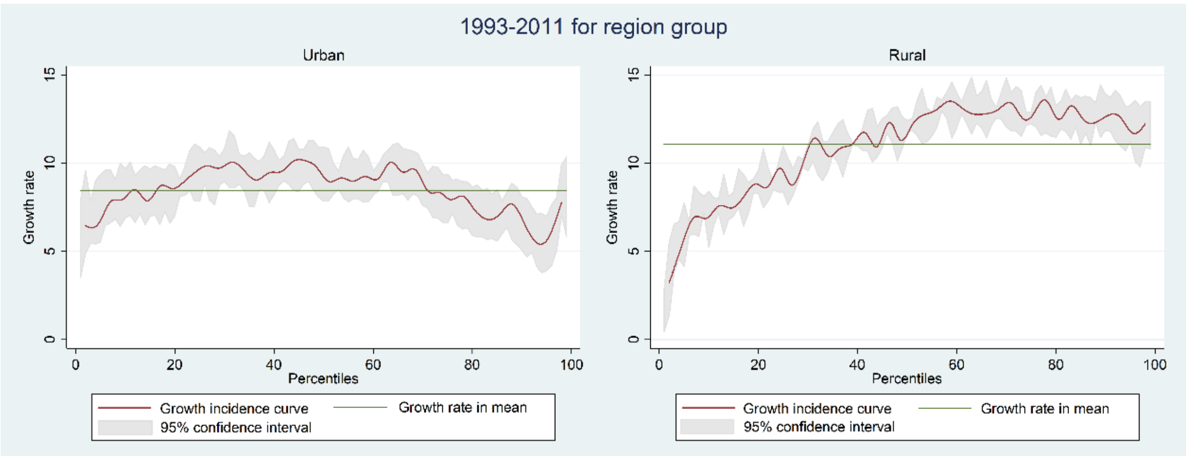

Fig. A8 WC growth incidence curves by region

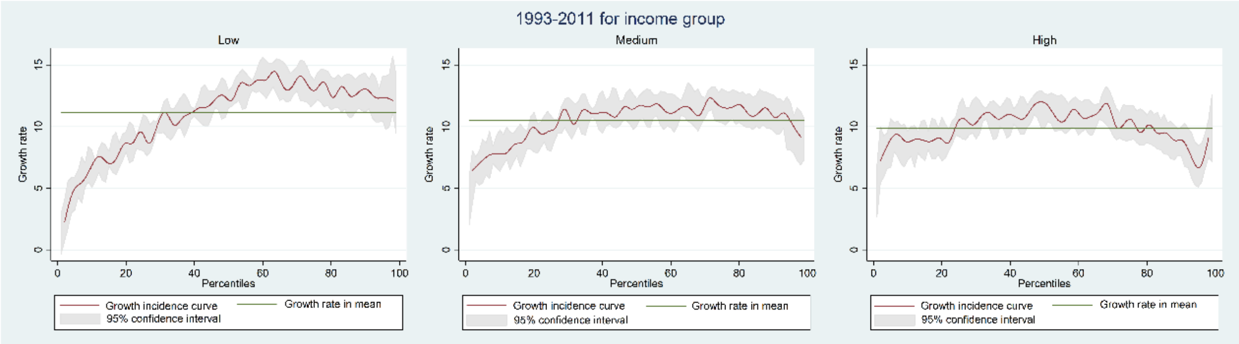

Fig. A9 WC growth incidence curves by income

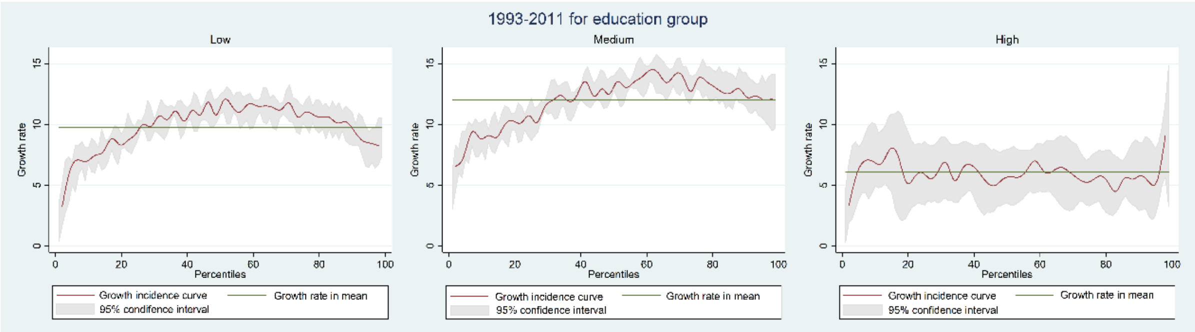

Fig.A10 WC growth incidence curves by education

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